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ConvLSTM based Spectrum Sensing Scheme for Cognitive Radio

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Abstract : Spectrum sensing is the key component for Cognitive Radio as it helps in finding the spectrum holes present on the spectrum. Now a days, Deep learning models shows promising result in finding the spectrum holes specifically CNN and LSTM network

A deep learning model with an architecture framework shows remarkable results in recent years. It is made up of numerous neural layers that represent data at different abstract levels has the ability to learn large signal data semantically at a high level, which can be a possible solution to all such problems. In this paper, the ConvLSTM network has been implemented with 64 filters and 128 cells per convolutional layer for spectrum sensing on a 2, 80,500 sample size dataset. The proposed model in the given scenario with Adam optimization shows the best performance for spectrum sensing when compared based on probability of detection (P_d), probability of false alarm (P_f), probability of miss detection (P_{miss}), and Signal-to-Noise ratio (SNR) with conventional techniques of spectrum sensing such as energy detection and eigen value detection.

Keywords: Cognitive radio, Spectrum sensing, Deep Learning, BILSTM network.

1. Introduction

Twenty years ago, Mitolla unveiled the Cognitive Radio (CR), a revolutionary idea in Wireless Communication Network (WCN) [1]. The foundation of CR is Soft Defined Radio (SDR) [2], in which specialized gear may be swapped out for more adaptable hardware that can be set up using software. Softly customizable and sensitive to the radio environment, CR can be used to maximize the usage of accessible spectrum bands while shielding occupied ones from harmful interference.

The majority of existing WCN has been built on fixed, or static, frequency assignments. They are intended to function within specific frequency ranges. Low spectrum utilization is the outcome of this static allocation, particularly during times of low traffic. According to [3], less than 15% of the allotted frequency bands are used. But in the current scenario, with technological advancements, real-time systems now require smooth data flow over networks. Hence, the WCN community is also being pushed to improve the utilization of the confined frequency resources in order to meet the growing demand for wireless communication services due to the emergence of 5G and future technological advances, the rapid increase in the variety of connected objects through the Internet of Things (IoT), Wireless Sensor Network (WSN) devices, and present wireless applications [4-5]. In the future, it appears that such a network will encompass the entirety of the earth's surface.

In order to tackle these problems of WCN, CR is devised as a viable option for completing Dynamic Spectrum Allocation (DSA) that utilizes the vacant frequency bands, also called "spectrum holes" [6-8]. This technique splits the users into two groups based on their ability to recognize these spectral possibilities: licensed or Primary Users (PUs) and unlicensed or Secondary Users (SUs).

SUs are constrained by the actions of PUs, whereas PUs has unrestricted access to the spectrum. Stated differently, SUs are not allowed to transmit detrimental interruptions from SUs to PUs and ought to honor the PUs' excellent service. As a result, three CR scenarios may be identified based on the likelihood that SU and PU transmissions would coexist in the identical channel, the SU transmit power that is allowed, and the collaboration among SU and PU. The three primary CR paradigms that can be identified are underlay access, overlay access and interweave access. In underlay access, the PU and SU may communicate concurrently using the exact same channel. Nevertheless, in order to maintain the interference on PU at a bearable level, the power that is transmitted must not exceed a specific threshold.[9]. In contrast to this, in overlay access, at the expense of acting as a relay for a number of PUs, the SU can transmit concurrently with the PU on an identical channel up to its maximum output power [10, 11]. In this instance, the SU relays the PUs while sending its own data. High levels of coordination

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among PUs and SUs are necessary for this sort of accessibility, which could compromise PU privacy.Finally in interweave access, only in the absence of PU is SU permitted to transmit at full strength. Because of its widespread use, this paradigm also referred to as the classical CR is the subject of this research.In the underlay paradigm, the low power transmission is a primary flaw, as it negatively affects throughput. The overlay paradigm can only be applied in situations where PU and SU work closely together. Under the interweave paradigm, SUs may transmit at the highest level of power, but at the expense of having to keep an eye on PU activity. Hence, Spectrum Sensing (SS) is a crucial problem for CR. The main reason behind the increase in complexity level of SS is the wireless channels' time-varying, fading, and shadowing characteristics. Many techniques for SS has already been introduced such as matched filtering [12], cyclostationary-based sensing [13-15], waveform-based sensing [16], wavelet-based sensing [17], eigen value-based sensing [18, 19], and energy detection sensing [20-22] to sense restricted or underutilized frequency bands.

The channel responsiveness has a major impact on this method's detection effectiveness. It need precise timing and synchronization in the media and physical access management layers to get around this. This circumstance makes the computation more difficult. Using the cyclostationary characteristics of the acquired signals, cyclostationary detection is a technique for identifying PU transmissions [18–20]. To determine whether PU is present, it takes advantage of the periodicity in the primary signal that was received. The detector can differentiate between PU signals, SU signals, and interference in this manner. Nevertheless, a substantial number of samples are required for this detection approach to function well, which raises the computational complexity. Waveform-based sensing is limited to structures that have established signal patterns [23]. When dealing with a well-established model, the spectrum detection function is executed by linking the received signal to a duplicate of the model. The wavelet transform is an effective tool for edge and singularity analysis. The frequency ranges of interest in the sensing method are typically broken down into a series of successive frequency sub bands [24].To conduct a hypothesis test, the selection threshold for the eigenvalue-based spectrum sensing approaches has been determined using random matrix theory. The test statistic, which is created by dividing the highest or mean eigenvalue by the smallest eigenvalue, is contrasted with the decision threshold to ascertain if the PU signal is present or absent. However, this method's considerable logistical complexity is a drawback. In a comparable manner, energy detection-based techniques with little mathematical and hardware complexity are preferred if the primary user information is unknown [25–26]. But this method has also faced many problems in SS, such as the longer sensing times needed for better detection reliability. Furthermore, a certain SNR must be reached in order to detect any signal.In the field of CR, deep learning approaches are utilized as a potent instrument to enhance the performance of SS [27–28]. It is possible to express SS as a binary classification problem associated with the existence of PU. Unlike standard SS, learning techniques have the potential to eliminate the requirement for knowledge of the PU signal or the channel's statistical properties. Additionally, these methods are suggested to forecast the PU activity, which can improve the secondary network's spectrum efficiency and shield the primary transmission from secondary interference.

DL is an architecture framework made up of numerous neural layers that may represent data at different abstraction levels. This makes DL an effective tool for addressing the issues with conventional systems. According to [29], DL offers a revolutionary approach because of its innate capacity to understand intricate patterns. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are the two prime models used under DL. CNNs are primarily made for image processing, but they are also capable of handling the spatial properties of RF signals and converting them into patterns that may be detected. However, RNNs are excellent at processing sequences, which makes them perfect for monitoring the temporal dynamics of spectrum utilization. When combined, these algorithms have the potential to completely transform spectrum sensing, allowing for more effective and flexible use of the radio frequency spectrum, satisfying the needs of contemporary wireless communication while optimizing spectrum resources. The same approach has been used in the present work. A general CNN framework has been presented in figure 1.

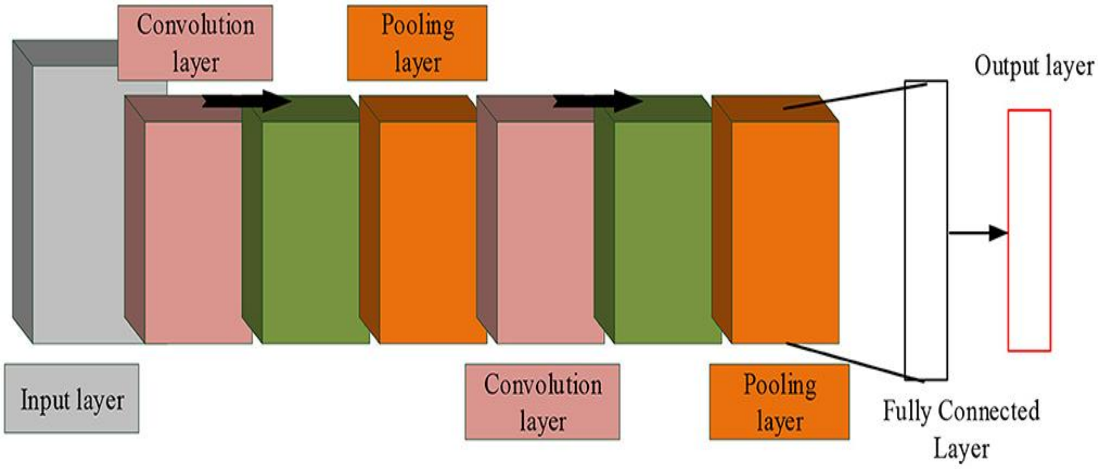


Figure 1: General framework of CNN

CNNs, which have their roots in image processing, are essential in many different applications because of their capacity to identify hierarchy patterns in data. Convolutional layers, which create feature maps by sliding (or convolving) a set of filters that can be learned over the input data (in this example, RF signals), are the fundamental building blocks of CNNs [30]. Pooling operations are applied to these feature maps in order to decrease their spatial dimensions while maintaining important information. The network is capable of identifying increasingly complicated patterns thanks to the stacked layers of convolution and pooling, which also help the network identify complex signal features in spectrum sensing [31]. When it comes to spectrum sensing, RF signals can be seen as one-dimensional "images" or sequences, which makes it possible for CNNs to efficiently extract spatial features.This feature makes it easier to identify subtle frequency usage patterns, which improves the accuracy of primary user detection under different spectrum settings. Because RNNs are designed to handle sequential input, they are highly suitable for jobs requiring memory or the taking into account of previous knowledge [32]. RNNs allow the network to retain some sort of "memory" about past inputs by feeding the output of one node back towards the net as an input [33]. RNNs are highly useful for applications involving time-series or sequential information because of their looping feedback mechanism, which enables them to analyze data sequences. RNNs are utilized in spectrum sensing with an emphasis on the temporal dimension of spectrum utilization. Because they can recall previous states, they are skilled at forecasting [34-35].Long Short-Term Memory (LSTM) networks are an example of an RNN variant that improves the storage capacity even further, making it possible to identify dependencies that persist in time-series data on spectrum utilization. Bi-Directional Long Short-Term Memory (BILSTM) is another variant of RNN. The architecture of the same has been presented in figure 2.

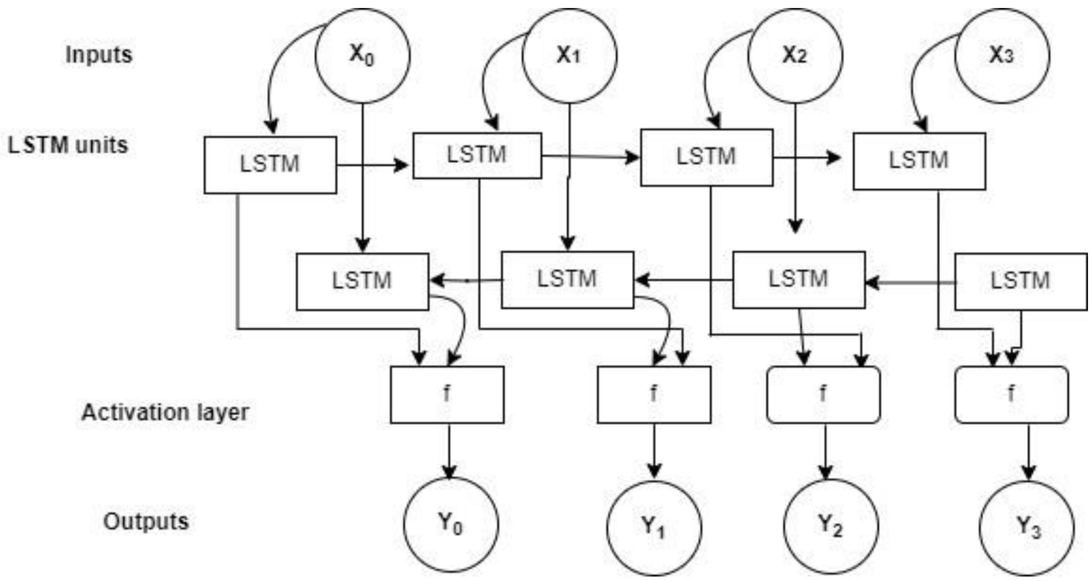


Figure 2: General architecture of BI-LSTM

An RNN layer that develops bidirectional long-term relationships among intervals of time-series or sequence information is called a BILSTM. The potential for Bi-LSTM to use upcoming contextual chunks to develop improved representations for the data kept it distinct from LSTM. In the present work the same has been deployed for SS. Table 1 represented the list of acronyms used in this article.

Table 1: Index of acronyms arranged alphabetically

Acronyms	Full Form
CR	Cognitive Radio
WCN	Wireless Communication Network
SDR	Soft Defined Radio
IoT	Internet of Things
WSN	Wireless Sensor Network
DSA	Dynamic Spectrum Allocation
PU	Primary User
SU	Secondary User
DL	Deep Learning
CNN	Convolutional neural networks
RNN	Recurrent Neural Networks
LSTM	Long short-term memory
BILSTM	Bi-directional long short-term memory
P_d	Probability Of Detection
P_f	Probability Of False Alarm
P_{miss}	Probability Of Miss Detection
SNR	Signal-To-Noise Ratio

2. Literature review

Author has conducted an extensive literature review on DL methods for spectrum sensing, and Table 2 summarizes the relevant papers and studies. The author in [37] has devised a CNN using one convolutional layer, which has been fed with a standardized cyclostationary and energy feature dataset and evaluated using PoD and SNR parameters. The results showed that PoD is 0.5 higher than CFD under -20 dB SNR. The author in [38] has devised a CNN using three convolutional layers known as deep cooperative sensing, which has been fed with sensing data that has been generated from multiple SU and evaluated using sensing error, ROC, and computational error. The results showed that the AUC for DCS with SD = 0.952 and DCS with HD = 0.95. The author in [39] has devised a CNN using two convolutional layers known as LeNet layers, which were further evaluated using PoD, ROC, and SNR parameters. The results showed that PoD is 96.7% under -18 dB SNR. The author in [41] has devised a CNN using one convolutional layer known as CNN-3, which has been fed with a 3.5 GHz spectrogram and evaluated using ROC and FROC. The results showed that the ROC had an accuracy of 0.994 and 0.998. The author in [42] has devised a CNN using one convolutional layer that has been fed with BPSK-modulated random bits with Rayleigh and Nakagami fading and evaluated using classification accuracy. The results showed a classification accuracy of 77.99% for Rayleigh and 77.333% for Nakagami. The author in [43] has devised a CNN using two convolutional layers and six residual blocks. The model has been fed a signal composed of eight modulation types and evaluated using PoD and SNR parameters. The results showed that PoD is 0.6 higher than CFD under 10 dB SNR. The author in [44] has devised a CNN with 85 layers, including convolutional and residual layers, called CRNet. The model has been fed with syntactically generated complex waveforms of PU signal and noise. The model has been evaluated using classification accuracy. The results showed a classification accuracy of 94.47%.have been fed with CM from the current frame and CMs from stacking from the past frame and evaluated using PoD and SNR parameters. The results showed that PoD is > 0.725 under -20 dB SNR. The author in [40] has devised a CNN using two convolutional layers based on LeNet-5 layers, which have been fed with samples, PU signals, Gaussian noise, etc., which

3. Research methodology

The research methodology devised for the current research work is shown in figure 4. It compose of three different stages, first is processing of model, models for spectrum sensing and evaluation of different models for SS. In first stage of processing of model, different steps to has been evolved including, dataset collection, dataset pre-processing, training dataset preparation, testing dataset preparation and model architecture design. In the second stage, for spectrum sensing, different models have been employed, including deep learning models such as BILSTM and conventional models such as energy detection and eigen value detection. Finally, in the third stage, a performance comparison has been made among all models simulated on the given dataset for spectrum sensing. In order to show the best performance for spectrum sensing, comparison has been made between different models based on probability of detection (P_d), probability of false alarm (P_f), probability of miss detection (P_{miss}), and signal-to-noise ratio (SNR).

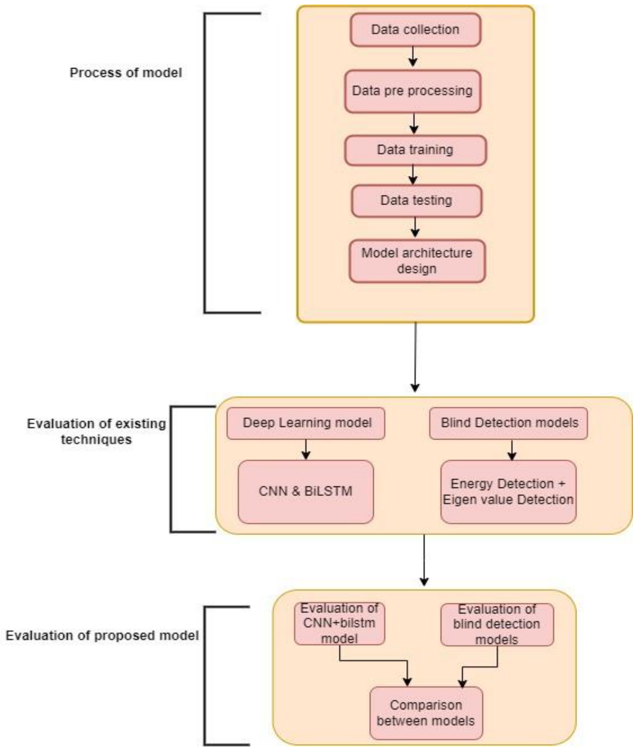


Figure 3: Flow chart of Research Methodology

3.1 Dataset collection

For simulation of the proposed models for spectrum sensing, the dataset has been prepared for 2, 80,500 samples using the algorithm given below.

Algorithm 1 Dataset generation

1: Rcv_signal y

2: Ensure: Dataset Y ← [y, label]

3: Procedure of Create Dataset (rcv_signal, N, Label)

frame_len← length(Rcv_signal)/ N (256byte)

noise_signal← AWGN with the power of −143dbm

PU_signal← BPSK signal

4: for SNR in −20dB ~ 10dB do

5: for i ∈ Monte Carlo simulation_num do (5000 times)

6: if Rcv_signal ← PU_signal + noise_signal

then label ← 1

snr_in_decimal← $10^{\frac{SNR}{10}}$

7: else if Rcv signal ←noise signal

8: Then Label ←0

End if

Return

End for

3.2 Dataset pre-processing

Usually, pre-processing is done on the raw signal data to adjust amplitudes, rescale, or carry out other required adjustments. By doing this, it can make sure the input data is appropriate for the proposed models.

3.3 Training data preparation

To train the CNN, a sizable collection of labeled signals is needed. Samples of both occupied and unoccupied frequency bands have to be included in this dataset. There are training and validation sets of the labeled data. For training the BILSTM model 60% of dataset has been employed in the present work.

Algorithm 2: Proposed Model Training

1. Procedure test (BILSTM, CNN_model, Dataset)

2. for i ← test_num do

Test_data, label ← extract (Dataset, 1)

H0_num ← 0 //(No. of samples with label 0)

H1_num ← 0 // (No. of samples with label 1)

H0_error_num ← 0 // (No. of errors for sample with label 0)

H1_correct_num ← 0 // (No. of corrected predication for sample with label 1)

Result ← predict (BILSTM, CNN, Dataset)

3. if label is 0 then

H0_num++;

4. if result is 1 then

H0_error_num++;

5. end if

6. end if

7. if label is 1 then

H1_num++

8. if result is 1 then

H1_correct_num++

9. end if

10. end if

$$P_d = \frac{H_1\_correct\_num}{H_1\_num}$$

$$P_f = \frac{H_0\_error\_num}{H_0\_num}$$

11. end for

3.4 Testing data preparation

For testing the BILSTM model, 20% of dataset has been employed in the present work.

3.4 Model architecture design

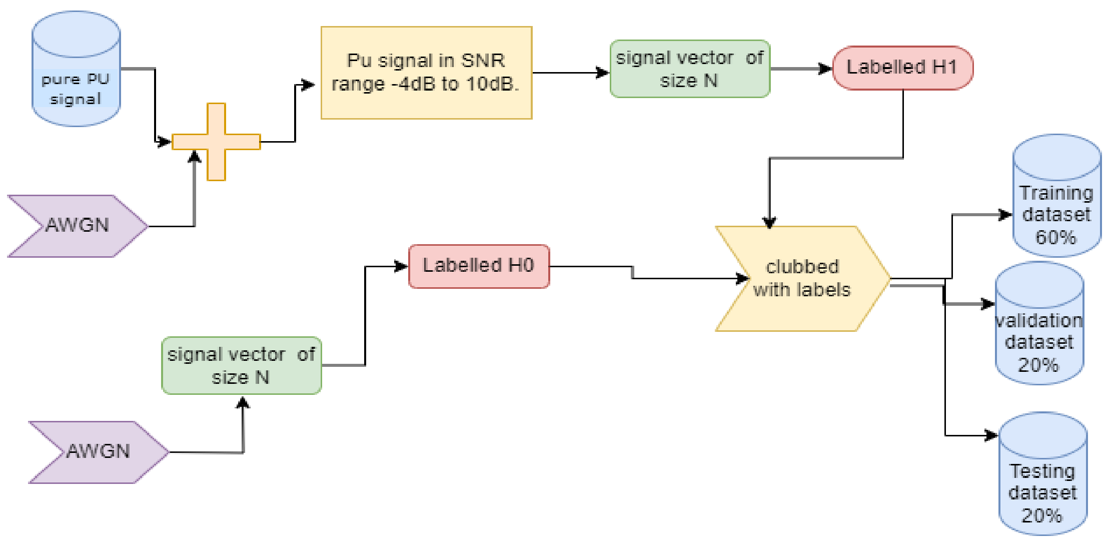


Figure 4: Process for model preparation

1. Input Representation:

The raw signal data is typically divided into fixed-length time windows or frames, where each frame contains a sequence of samples.

Each sample in the sequence is considered as an input at a particular time step.

2. Hidden State Update:

At each time step t, the BILSTM takes the input sample at that time step, along with the previous hidden state, and computes a new hidden state.

The hidden state is updated using a combination of the current input and the previous hidden state, applying an activation function to capture the non-linear relationships between the inputs and

3. Output Generation:

Output is generated at final stage only. The output is prediction of whether the frequency band is occupied or unoccupied.

3.5 Framework of models

Three different deep learning models have been employed in this work for dataset simulation. The names of the models are CNN and BILSTM, and the proposed model is named ConvLSTM. The architectural framework of all these models has been presented below.

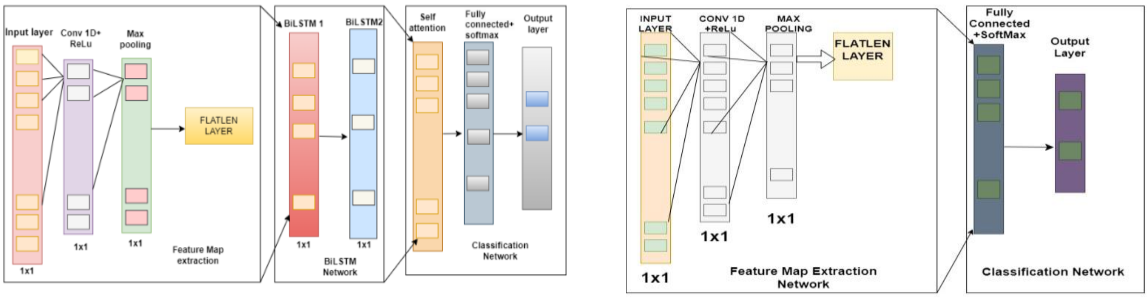


Figure 6: Architectural framework of CNN

The CNN has been designed with an input layer, convolution layers, and a fully connected layer. Each layer has used a 1x1 feature map.

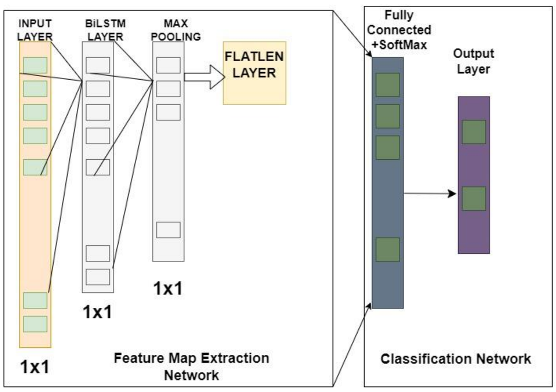
CNN can extract spatial features of data, it is made up of sparse connection, pooling and weight sharing. A feedforward CNN consist of an input layer, hidden layer and output layer. The operation of a convolution layer is given below where

$W_{HxH} \in R(H \times H)$ is the weight matrix for the recurrent connections, $W_{hx} =\in R^{(H\times H)}$ is the weight matrix for the input connections, $b_h \in$

$$H_t = f(W_{H\times H} * h_{t-1} + W_{hx} * x_t + b_{th})$$

3.5.1 Architectural framework of BiLSTM

Architectural framework of BiLSTM has been presented below.



The BiLSTM has been designed with an input layer, BiLSTM layers, and a fully connected layer. Each layer has used a 1x1 feature map.

A mathematical model for RNNs in spectrum sensing involves capturing the computations performed at each time step and the update rules for the hidden state. Here's a mathematical formulation of a basic RNN model for spectrum sensing: $X_t \in R^D$ represents the input signal at each time step t, where D is the number of input features. The hidden state $h_t \in R^H$ at time step t is

computed as a function of the input signal and the previous hidden state:

The BiLSTM has been designed with an input layer, BiLSTM layers, and a fully connected layer. Each layer has used a 1x1 feature map.

3.5.2 Architectural framework of ConvLSTM

The learning or training parameters of the model have played a significant role in the model's performance. Hence, after a rigorous process, the following training parameters have been chosen for the proposed model as represented by table

Table 4: Training parameters of the model

Parameters	Value
Input Shape	2,80,500
Activation Function	ReLu
Monte Carlo simulation	5000
Drop out ratio	0.20
SNR range	-20dB to 10dB
Initial learning rate	0.001
Filters per convolution layer	64
Cells per LSTM layer	128
Optimizer	Adam
Metrics	Probability of detection (P_d), probability of false alarm (P_f), probability of miss detection (Pmiss), and signal-to-noise ratio (SNR)

4. Dataset generation

In this paper, The dataset for training and testing is generated under different SNR level, after that Monte Carlo simulations is carried out 5000 time at each SNR. The noise received by each SU is additive white Gaussian noise with mean value 0 and noise power leveled -143dbm/Hz [ ] the same power. It is assumed that the noise power does not change during the whole spectrum sensing period.

Simulation and result analysis

For spectrum sensing, the suggested dataset has been tested using deep learning and conventional models such as energy detection and eigen value detection. The feed-forward and feed-backward BILSTM models were created for this purpose. A variable learning rate was also picked for the model to test. On an Hp personal laptop with 12 GB of RAM and 32 GB of ROM, the model was tested. MATLAB 16 was used to construct the model's pyramiding. Below is a detailed results analysis of the suggested work.

4.1 Simulation results analysis of Energy Detection algorithm

The dataset was first simulated using an energy detection algorithm. For testing the performance of the energy detection algorithm, various matrixes have been employed, such as probability of detection (P_d), probability of false alarm (P_f), probability of miss detection (P_{miss}), and signal-to-noise ratio (SNR). The results in terms of graphical representation have been presented below in figures 9 and 10. The P_d is a statistical measure that signifies the probability of correctly detecting the existence of a signal in the presence of noise.

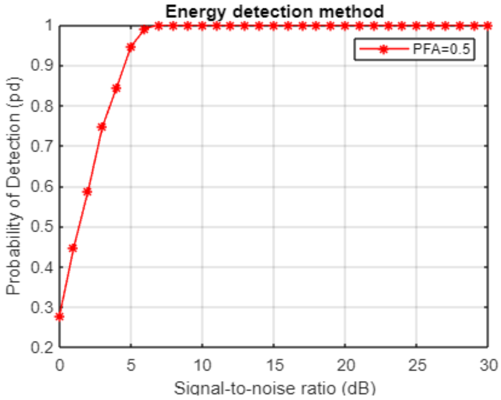


Figure 9: Graphical representation of Energy Detection algorithm for probability of detection (Pd)

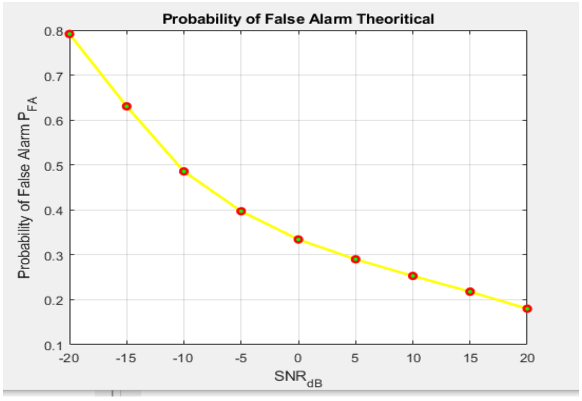


Figure 10: Graphical representation of energy detection algorithm for probability of false alarm (P_f)

As per the analysis from figure 9 of probability of detection (P_d), for the energy detection algorithm, the P_d has been increased from 0.23 to 1 from the SNR value of 0 dB to 6.5dB. On the other hand, when observed for probability of false alarm (P_f), the value of P_f has been decreased from 0.8 to 0.188 as the SNR value changed from -20 dB to 20dB.

4.2 Simulation results analysis of Eigen value detection algorithm

Data noise can be decreased by using eigen values. They can aid in increasing our productivity on computationally demanding jobs. They also assist in lowering over-fitting and remove elements that exhibit a high association with one another. Eigen value detection performs better when the PU's signals are highly correlated and solves the noise uncertainty issue. A simulation of the dataset was further performed with an eigen values detection technique. Numerous matrices, including signal-to-noise ratio (SNR), probability of false alarm (Pf), probability of miss detection (Pmiss), and probability of detection (Pd), have been used to measure the eigen value detection performance. The graphical depiction of the results is shown in figures 11 and 12 below.

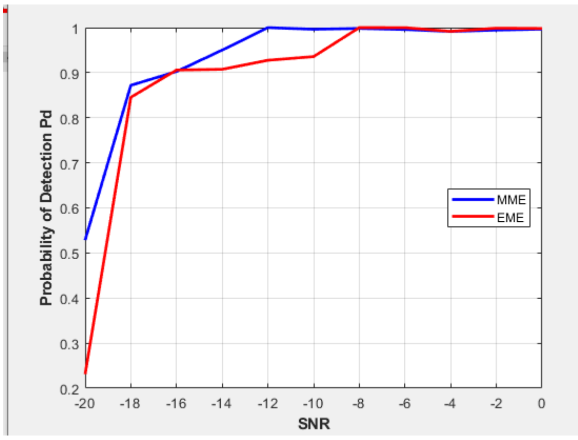


Figure 11: Graphical representation of Eigen value detection algorithm for probability of detection (P_d)

4.3 Simulation results analysis of Comparison of Blind Detection algorithms

The comparison of MME detection and energy detection performance in terms of probability of detection and SNR is plotted in fig 12. It is observed that hybrid (MME & ED) technique outperforms single blind spectrum technique. When Eigen value detection is combined with energy detection the probability of detection 1 is achieved at SNR 6dB.

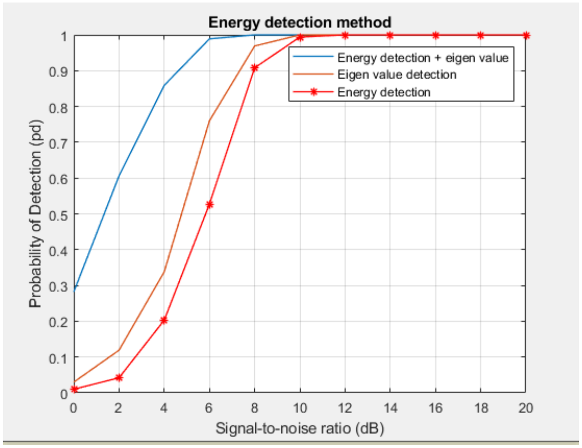


Figure 12: Comparison performance of all three blind spectrum sensing techniques

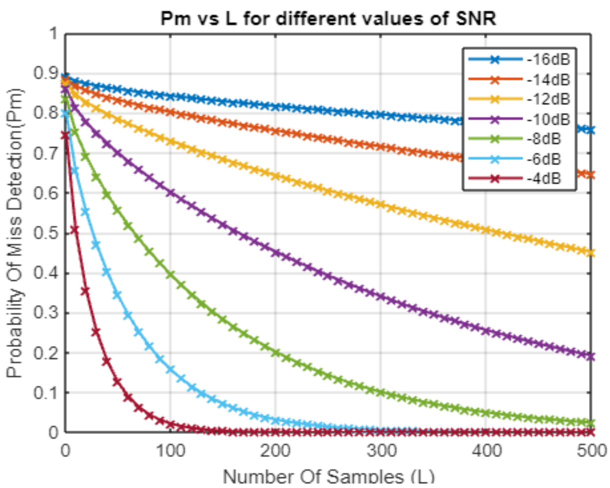


Figure 12: Graphical representation of Eigen value detection algorithm for probability of miss detection (Pmiss)

Figure 11 shows many probability of detection (Pd) values for different SNR values for (Maximum - Minimum Eigen value) MME and EME (Energy with Minimum Eigen value). MME outperforms EME in case of probability of detection. Figure 12 shows a graphical representation of the eigenvalue detection algorithm for probability of miss detection (P_{miss}). It has been observed that for -16 SNR, the probability of miss detection (P_{miss}) is 0.85 for up to 100 samples and reduced to 0.74 for up to 500 samples. Further if observed for SNR = -4, the value of probability of miss detection (Pmiss) has reduced to 0. With the increase of SNR probability of missed detection starts decreasing with increased number of samples.

4.3 Simulation results analysis of CNN algorithm

The CNN model was ultimately used to simulate the dataset. Numerous matrices, including signal-to-noise ratio (SNR), probability of detection (Pd), probability of false alarm (Pf), probability of miss detection (Pmiss), and probability of detection (Pd), have been used to test the CNN algorithm's performance. Figures 13 and 14 below show the results as they are represented graphically.

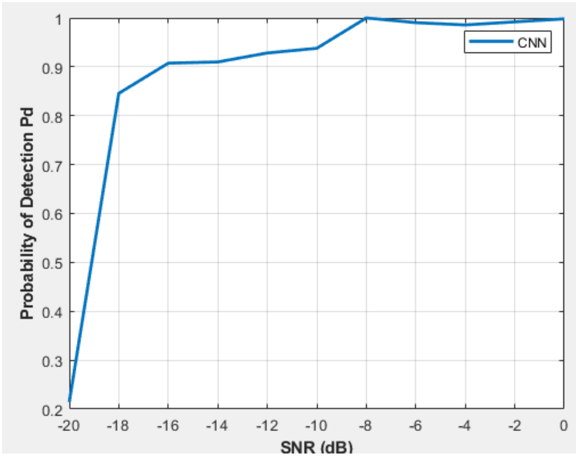


Figure 13: Graphical representation of CNN algorithm for probability of detection (P_d)

It has been observed that for BILSTM algorithm probability of detection (P_d) has been improved from 0.7 to 1 with SNR value vary from -17db to -8 db.

4.3 Simulation results analysis of BILSTM algorithm

The dataset was finally simulated using BILSTM algorithm. For testing the performance of the BILSTM algorithm, various matrixes have been employed, such as probability of detection (P_d), probability of false alarm (P_f), probability of miss detection (P_{miss}), and signal-to-noise ratio (SNR). The results in terms of graphical representation have been presented below in figures 13 and 14.

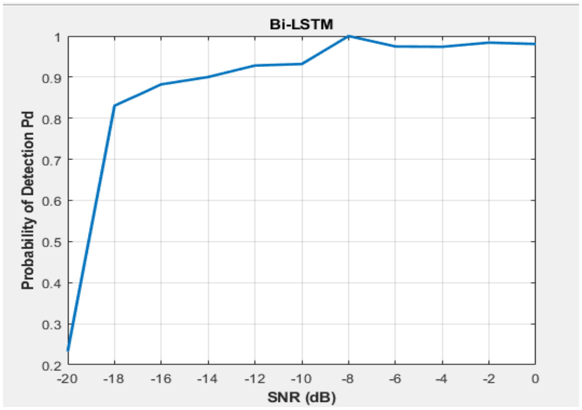


Figure 13: Graphical representation of BILSTM algorithm for probability of detection (P_d)

It has been observed that for BILSTM algorithm probability of detection (P_d) has been improved from 0.8 to 1 with SNR value vary from -18db to -8 db. Other than this, the impact of power on the probability of detection (P_d) of BILSTM algorithm has been observed for different power values. In figure 13, impact of power on the probability of detection (P_d) of BILSTM algorithm under -5db SNR has been shown.

4.4 Simulation results analysis of proposed algorithm (ConvLSTM)

Fig 14 shows the ROC curve of proposed (ConvLSTM) model. The experiment is carried out to estimate the performance of proposed model. The CNN model is used with extra layer called self-attention layer to capture the dependencies between the input signals without extra computation. The algorithm with a higher detection probability and lower false alarm probability has better detection performance. In fig 14 the

probability of detection 1 is achieved at SNR -12dB. The detection performance of proposed model outperforms all other models in terms of low SNR and detection probability.

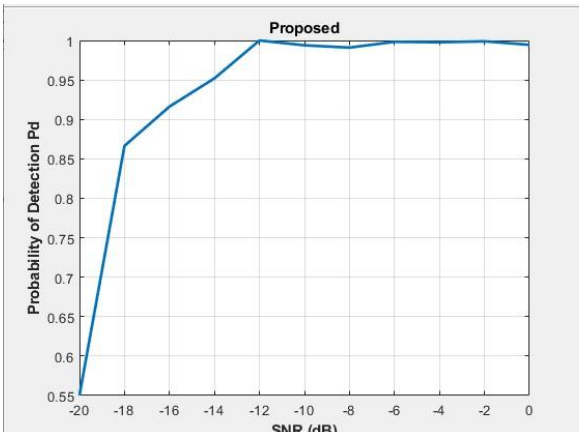


Figure 14: Graphical representation of Proposed (ConvLSTM) model for probability of detection (P_d)

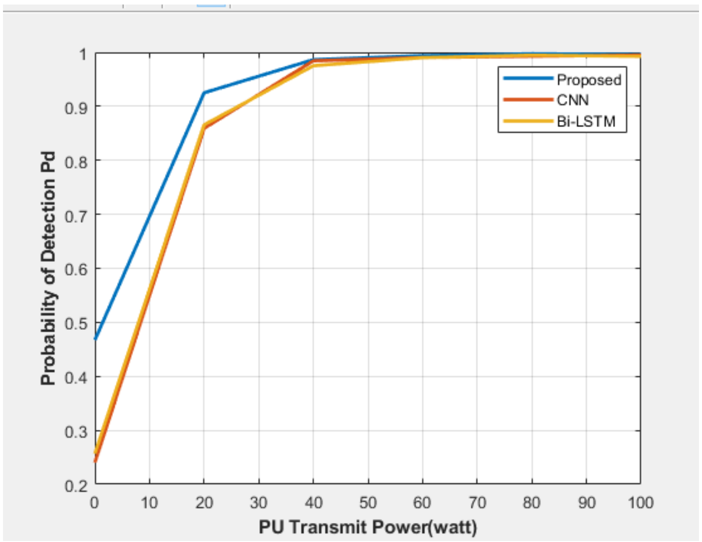
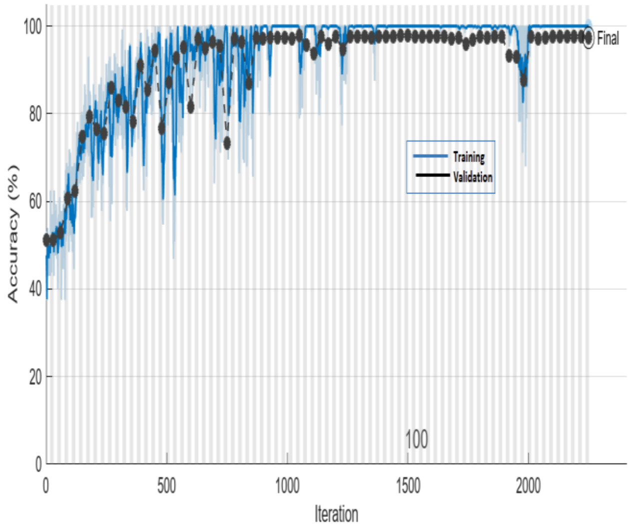
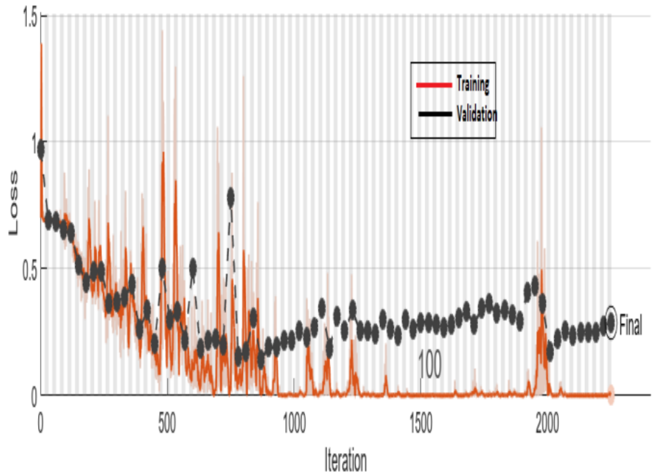


Figure 15: Graphical representation of different techniques for probability of detection (P_d) Vs

PU transmit power under SNR -5db.Fig 15 shows the graph of Primary user transmit power of all three techniques. It is observed that proposed technique ConvLSTM shows high detection probability even in low PU transmit power as compared to other techniques. Other than, accuracy and loss graph for proposed ConvLSTM has been shown in figure 16.



(a)



(b)

Figure 16: ConvLSTM (a) Accuracy graph (b) Loss curve

Figure 15, has shown the performance of proposed BILSTM model in term of its accuracy and loss analysis. It has been observed that the BILSTM model for spectrum sensing has been improved for accuracy with value 0.50 to 0.99 when iteration has been increased from 0 to 1000.

Fig 16 shows the detection performance of the proposed algorithm for different number of SUs and specified false alarm rate of 0.01. From the figure, it can be clearly seen that there is a significant increase in P_d with number of secondary users. In the considered simulation scenario, the detection performance of proposed algorithm shows significantly higher results as compared to CNN and Bi-LSTM.

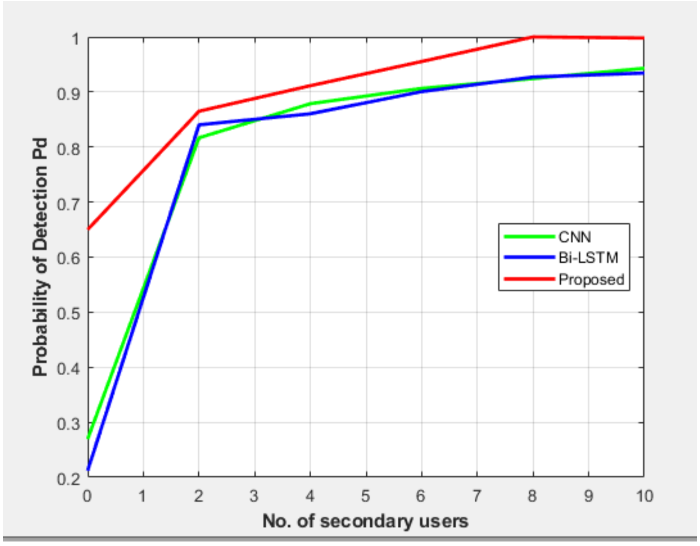


Fig 16: Probability of Detection with different no. of secondary users

5. Conclusion

The crucial task of a cognitive radio system is spectrum sensing, which permits an unlicensed user, referred to as a SU, to access the spectrum while the licensed user, referred to as a PU, is not using it. The author in this paper, has integrated deep learning model with spectrum sensing to examine the detection probability. In this paper, author implemented various models, including the deep learning model called BiLSTM and convolutional model on various parameters. Various conventional models such as energy detection and eigenvalue detection have been also implemented for detection comparison. The authors have examined how all these models have been performed for spectrum sensing and expressed themselves by estimating various parameters, including probability of detection (Pd), probability of false alarm (Pf), probability of miss detection (Pmiss), and signal-to-noise ratio (SNR). Deep learning algorithms, have the capacity to adapt and generalize well to different signal types and environmental conditions. This flexibility leads to improved detection accuracy, even in scenarios with challenging and diverse spectrum conditions. One of the key advantages of deep learning algorithms is their ability to handle complex and non-linear relationships within the spectrum data. The integration of DLM like CNNs and RNNs into spectrum sensing showcases promising results, but the horizon for future exploration in this domain remains vast. Further, It is concluded that exciting developments in the field of spectrum sensing with BILSTM are about to occur, paving the way for groundbreaking advances in cognitive radio networks.

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